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Many-objective optimisation tool for the design of district metered areas in pumped water distribution networks

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ABSTRACT

The establishment of district metered areas (DMAs) is a highly effective method to mitigate operational management difficulties and enhance the efficiency of water distribution networks (WDNs). There are several objectives associated with the DMA's design that are contingent upon the network parameters that are affected by its formation. Two previous studies considered DMA design as a three-objective problem (operational cost, average pressure and water age) and a four-objective problem (design cost, pressure deviation, resilience index (RI) and demand shortfall) for pumped and gravity networks, respectively. The problems were addressed through the implementation of a multi-phase DMA design methodology using the NSGA-II and NSGA-III optimisation tools, respectively. The present work builds upon previous research by simultaneously considering five objectives in DMA design (i.e. design cost, operational cost, RI, average pressure and water age) using the NSGA-III optimisation tool in pumped water networks. In this extended approach, the pump's role in meeting nodal demands eliminates the necessity of including demand shortfall as one of the objectives. The proposed methodology has been evaluated on two benchmark networks, demonstrating its capability to identify DMA alternatives and provide solutions based on user preferences. Finally, the obtained results are compared with the previous study's findings.

Key words: district metered areas, fast Newman algorithm, many-objective optimisation, multiple attribute decision-making, NSGA-III algorithm

HIGHLIGHTS

- Use of many-objective optimisation tool for DMA design in pumped water networks.
- Consideration of design and operation cost in a single optimisation framework along with the hydraulic and water quality parameters.
- Use of pressure as pipe weights in clustering phase to get pressure-based partitioning of water network.
- Use of decision-making tool for identifying a unique solution from a set of feasible solutions.

1. INTRODUCTION

A water distribution network (WDN) is an essential municipal infrastructure designed to meet the daily water needs of a city. Water utilities must adhere to strict regulatory standards in order to provide adequate water and maintain appropriate service levels (Morrison *et al.* 2007). However, due to their complex nature, the operation and management of networks can be a tedious task. An effective solution to the problem is to divide the system into subsystems, i.e. district metered areas (DMAs), which have defined permanent boundaries. By monitoring the quantities of water entering and leaving these areas, operational maintenance becomes easier (Bui *et al.* 2020). The design of DMAs has multiple attributes, such as facilitating pressure and leakage control (Laucelli *et al.* 2017), protecting water quality (Armand *et al.* 2018), enabling real-time monitoring of inlet and outlet flows in each subsystem through water balance analysis, using pumps as turbines (PAT) for energy recovery (Lima *et al.* 2018) and detecting pipe bursts (Huang *et al.* 2018), among others.

The primary objective of designing WDNs is to ensure maximum customer satisfaction by supplying an adequate quantity of water that meets acceptable quality standards and is delivered at adequate pressure levels (Zeidan *et al.* 2021). However, when partitioning the network into DMAs, it is necessary to close a few boundary pipes to minimise interconnections between the different DMAs. The closure of boundary pipes for DMA identification may reduce the reliability of the water network (Mu *et al.* 2021). When boundary pipes are closed, the water inside the network must take a longer route to reach the demand nodes (Sharma *et al.* 2022b). This results in increased head loss (Di Nardo *et al.* 2014) and extended retention time in the water network. Thus, the designer needs to ensure that the cost of implementation (cost of flow meters and isolation valves) is minimised without compromising customer satisfaction (i.e. low demand deficit) (Sharma *et al.* 2022a). The design problem of the DMAs is cascading in nature, where managing one parameter leads to the slippage of another parameter, and so on. Focusing on only one parameter of the DMA's design may not be sufficient in such a case. Therefore, researchers are emphasising the design of DMAs as a multi-dimensional problem with a few independent parameters (design and operational cost) and a few dependent parameters (reliability/resilience, customer satisfaction and water quality).

The search for a fair DMA layout in a given network is a complicated process and involves three phases: (a) zone planning or clustering, (b) boundary optimisation or sectorisation and (c) performance evaluation of the optimal solution (Sharma *et al.* 2022a). The goal of the clustering phase is to group the nodes into DMAs of uniform size while minimising the number of boundary pipes that connect the adjacent DMAs. In this regard, several approaches, such as multi-agent systems (Herrera *et al.* 2012), graph theory (Di Nardo & Di Natale 2011), cluster analysis (Liu & Han 2018) and community detection algorithms (Diao *et al.* 2013; Zhang *et al.* 2017), can be useful. A comparison of these algorithms can be found in the study conducted by Bui *et al.* (2020). In the sectorisation phase, physical separation between the communities is achieved by installing flow meters and isolation valves at appropriate locations. This phase is addressed by using various iterative methodologies that involve repeated cycles of designing, analysing and refining the network layout and components to meet specific DMA design objectives (Alvisi 2015; Pesantez *et al.* 2019; Zevnik *et al.* 2019; Vasilic *et al.* 2020). Various heuristic techniques considering the design of DMAs as a single-objective problem (Di Nardo *et al.* 2014; Shao *et al.* 2019) or a multi-objective problem (Hajebi *et al.* 2015; Campbell *et al.* 2016; Laucelli *et al.* 2017; Zhang *et al.* 2017; Creaco *et al.* 2019; Brentan *et al.* 2021; Zeidan *et al.* 2021; Sharma *et al.* 2022b) can also be used for network sectorisation. The choice of objectives depends on the broad aim of DMA design, such as minimising leakages, maintaining water quality or regulating pressure. It also depends on the nature of the water network, whether it is a gravity-based system or a pumped system (either partially or fully pumped). For design problems related to DMA gravity networks, it is important to prioritise the objective of a demand shortfall or unsupplied demand. This is because the closure of pipes can lead to a drop in pressure. On the other hand, for pumped networks, the focus should be on pump energy costs and surplus pressure. Excessive pumping and high pressure can result in increased background losses and operational costs. For multi-objective DMA design studies, a variety of feasible solutions are obtained at the end. However, finding a unique solution out of a set of feasible solutions can be tedious. In such cases, multiple attribute decision-making (MADM) tools (Rao 2007) are generally adopted to prioritise each objective based on its relevance in the study. Weightage is assigned to each objective accordingly in order to arrive at a final solution. It is also important to mention that the nature of the objectives affects the method of hydraulic analysis used in the sectorisation phase. For example, pressure-driven analysis (PDA) is essential for assessing the total demand shortfall when specific boundary pipes are closed, while demand-driven analysis (DDA) is needed to assess any pressure deficiency caused by the closure of a valve.

The present study is an improvement over previous works by Zeidan *et al.* (2021) and Sharma *et al.* (2022b). Both of these studies utilised the three-phase DMA design methodology, which involved the clustering of the network using the fast Newman algorithm (FNA), followed by the sectorisation of the network using an optimisation tool, and lastly, the performance evaluation of the obtained DMA configuration. Zeidan *et al.* (2021) formulated the design problem of DMAs as a multi-objective optimisation problem, where three objectives were optimised: (a) operational cost, (b) average pressure and (c) water age. The optimisation problem was solved using the non-dominated sorting genetic algorithm-(NSGA-II) algorithm. The study did not consider the cost of design (including flow meters and isolation valves) or the resilience index (RI) in the formulation of the optimisation problem. The RI (Todini 2000) is used as a surrogate measure of network reliability. As the design of DMAs involves closing off certain boundary pipes, the hydraulic performance of the network is altered. Thus, it is essential that even after partitioning, the network is able to meet the demand and maintain the desired pressure at all nodes throughout its design period. The aspects of design cost and RI were considered by Sharma *et al.* (2022b) in a multi-objective DMA design problem with four objectives: (a) design cost (including the cost of flow meters and isolation valves), (b) pressure deviation, (c) RI and (d) total demand shortfall for gravity networks. The NSGA-III algorithm was used as an optimisation tool. In the current paper, the methodology is extended to the design problem of DMA in pumped networks. The unique feature of this work is the application of the NSGA-III algorithm in the sectorisation phase, where the design cost and the pump operational cost are simultaneously addressed within a single framework. The algorithm solves five objectives of DMA design, namely the design cost (number of flow meters), operational cost (pumping cost), RI, water age and average pressure. This is achieved by incorporating two types of variables into a single chromosome: binary variables for pipe status and actual variables for pump scheduling. In this work, the DDA is used for hydraulic analysis within the optimisation framework, as pumps provide extra head to satisfy the demand. The aim of this study is to provide an in-depth analysis of various feasible solutions for water utilities and to facilitate decision-making by employing an appropriate decision-making process. The obtained results indicate that the present method can provide satisfactory solutions in the majority of cases. The overall description of the methodology is presented in the next section.

2. METHODOLOGY

The proposed methodology consists of three steps: (a) clustering phase, (b) sectorisation phase and (c) MADM with performance evaluation of results. The clustering phase (Section 2.1) provides an initial set of nodes that can be grouped together into a single DMA. This phase also offers a set of boundary pipes or interconnected pipes between adjacent clusters. In the next step, which is the sectorisation phase (Section 2.2), permanent boundaries are established among different DMAs. This is done by closing certain boundary pipes, taking into consideration economic factors (design and operational cost), hydraulic factors (RI and average pressure) and quality factors (water age). The objective of sectorisation is to achieve these goals. This is accomplished using a many-objective optimisation tool, specifically the NSGA-III algorithm. The sectorisation phase results in multiple viable solutions. In order to arrive at a unique solution from a set of feasible options, this work employs the MADM tool. MADM requires user input to assign weights to each objective of DMA's design. The weight assignment methodology is explained in Section 2.3.

2.1. Cluster identification

In the clustering phase, the WDN was mapped into an undirected graph, $G = (V, E)$, where V represents the vertices (demand nodes, tanks and reservoirs) and E represents the edges (pipes, valves and pumps). The FNA (Clauset *et al.* 2004) was used in this study to subdivide the graph G into several clusters. The algorithm is fast and efficient, working on the principle of grouping vertices together based on a high density of edges within each group while keeping the connections between groups sparse. The algorithm uses modularity (Q) as an indicator to identify the quality of partitioning. The value of Q ranges from 0 to 1, where higher values of Q indicate a higher quality of clustering. Modularity (Q) can be expressed mathematically as:

$$Q = \frac{1}{2m}\sum_{\upsilon\omega}\left[A_{\upsilon\omega} - \frac{k_\upsilon k_\omega}{2m}\right]\delta(C_\upsilon, C_\omega) \tag{1}$$

where $A_{\upsilon\omega}$ represents an element of the adjacency matrix of the network ($A_{\upsilon\omega} = 1$, if vertices υ and ω are connected; otherwise, $A_{\upsilon\omega} = 0$); $m = \left(\sum_{\upsilon\omega} A_{\upsilon\omega}\right)/2$ total number of edges; $k_\upsilon = \left(\sum_{\omega} A_{\upsilon\omega}\right)$ = degree of vertex υ, defined as the number of edges connected to that vertex; $\delta(C_\upsilon, C_\omega) = 1$, if $C_\upsilon = C_\omega$ (otherwise = 0); C_υ and C_ω are two different communities; υ and ω are vertices in C_υ and C_ω, respectively; and $k_\upsilon k_\omega/2\,\mathrm{m}$ = probability of an edge existing between vertices υ and ω, if connections are randomly made (respecting vertex degrees). The steps involved in the algorithm are as follows:

1. Initially, each node functions as an independent community, and the modularity for this state is calculated.
2. The equation used to calculate the change in modularity ($\Delta Q_{\upsilon\omega}$) for each combination of vertices υ and ω is as follows:

$$\Delta Q_{\upsilon\omega} = \begin{cases} 1/2m - k_\upsilon k_\omega/(2m)^2, & \text{if } \upsilon \text{ and } \omega \text{ are connected} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The pair of nodes with the highest change in modularity are merged and grouped together in one community. The modularity of the new configuration is equal to the sum of the modularity of the old configuration and the maximum change in modularity.

3. The steps are repeated until all the vertices have been merged into a single community.

The algorithm has been graphically presented with a basic example consisting of 6 vertices and 10 edges. Unit weights have been assigned to the edges, although different weights can be assigned based on the specific problem requirements. Figure 1(a)–1(e) shows the step-by-step formation of communities.

The dendrogram representation of the procedure is shown in Figure 1(f). A dendrogram is a tree-like structure used to illustrate the hierarchical formation of clusters. It helps decision-makers determine the number of clusters required for a particular graph.

2.2. Sectorisation of the water network

After the tentative clusters are formed, and the boundaries are identified, the next step is to determine the status of the boundary pipes. This ensures that the overall hydraulic performance of the network remains satisfactory even when a few pipes are closed. The sectorisation phase is framed as an optimisation problem with five different objectives to be minimised/maximised, depending on the nature of the objective functions.

2.2.1. Objective functions

The design of the DMAs has been considered a multi-objective optimisation problem in this phase, considering five objectives. The optimisation model is solved using the NSGA-III algorithm while adhering to a set of constraints. The objectives are discussed as follows:

2.2.1.1. Number of flow meters required. The most common design aspect of DMAs is to minimise the capital costs associated with installing flow meters and isolation valves. The number of flow meters is minimised in this work as a proxy for the capital cost of devices. The capital cost, on the other hand, does not reflect the most critical design criteria that should be evaluated for DMAs. Mathematically, it is expressed as:

$$\mathrm{Min(CF)} = \sum_{n=1}^{n_\mathrm{p}} N_\mathrm{fm} \tag{3}$$

in which N_fm is the number of flow meters; n_p is the number of potential boundary pipes; and CF is the cost function

2.2.1.2. Operational cost. When designing the DMAs for a pumped network, it is necessary to consider the cost of pumping. The operational cost reflects the energy costs associated with pumping to meet the demand and maintain tank level control.

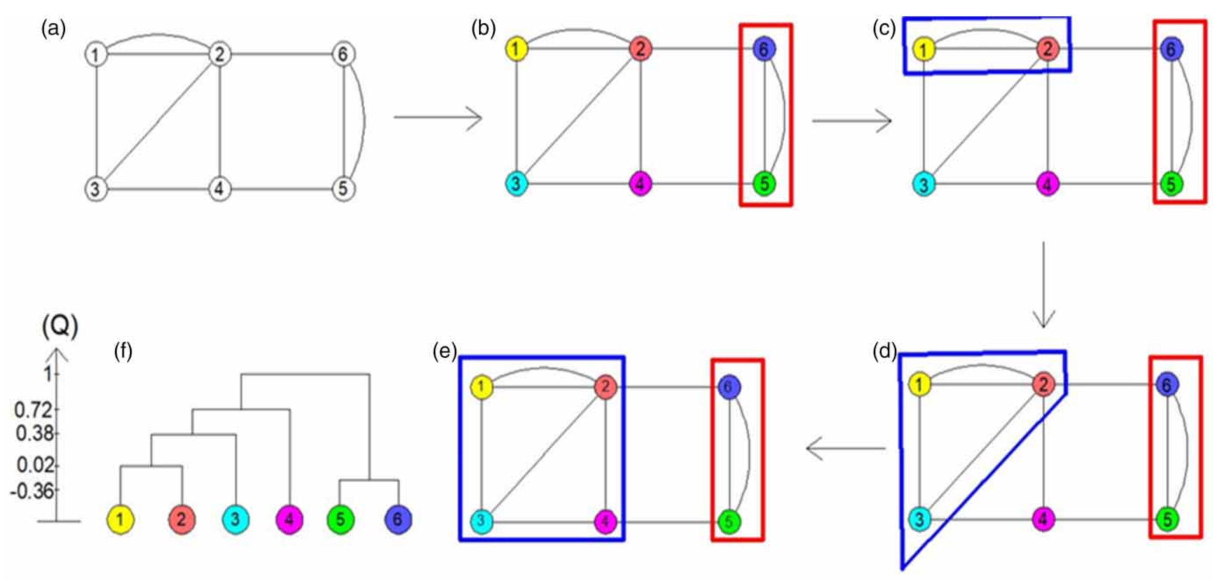

Figure 1 | Application of FNA on a simple unweighted graph.

It is assumed that adjustable frequency drives (Zeidan *et al.* 2021) are attached to the pumps, enabling control over the speed and power of the pump. Mathematically, the problem of minimising operational costs can be defined as:

$$\text{Min (Operational Cost)} = E_c \sum_{j=1}^{k} \sum_{i=1}^{T} \varphi_{j,i} P_{j,i} \tag{4}$$

where E_c is the electricity cost (\$/kW-h); φ is the tariff coefficient; P is the pump's power (kW); k is the number of pumps; and T is the number of time steps during the simulation.

2.2.1.3. Resilience Index (RI). The ratio of available power to supplied power is referred to as the network's resilience. The optimisation of DMA boundaries involves closing a few pipes to establish permanent boundaries. When pipes are closed, water takes longer and follows alternative routes to reach a demand node, which alters the network's layout. It results in significant friction losses and reduced resilience.

While designing the DMAs, the RI should be maximised. While this conflicts with the DMA's pipe closure activity, maximising RI ensures that the system does not exceed certain limits and loses available power. Mathematically, it is expressed as (Todini 2000):

$$\text{Max (RI)} = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{n=1}^{nn} q_j (h_{a,j} - h_{r,j})}{\sum_{sr=1}^{nr} Q_{sr} H_{sr} + \sum_{sp=1}^{np} \frac{P_{sp}}{\gamma} - \sum_{n=1}^{nn} q_j h_{r,j}} \tag{5}$$

where nn is the number of demand nodes; np is the number of pumps; nr is the number of reservoirs; q_j is the demand at node j; $h_{a,j}$ is the available head at demand node j; $h_{r,j}$ is the required head at demand node j; Q_{sr} is the supply at reservoir sr; H_{sr} is the head at reservoir sr; P_{sp} is the power from pump sp; γ is the specific weight of water (KN/m^3); and RI is the average resilience index.

2.2.1.4. Average pressure. The primary factor that contributes to pipe bursts or network leaks is high water pressure. Since the pressure acts as a proxy for the leakage reduction problem (due to the pressure-leakage relationship), it becomes necessary to minimise excessive pressure in the network (Schwaller *et al.* 2015). It also helps to ensure customer satisfaction during daily operations and minimise leakages by regulating the system pressure. The mathematical expression for the minimisation problem of average pressure at all demand nodes during the total simulation period is as follows:

$$\text{Min (average pressure)} = \frac{1}{nn\ x\ T} \sum_{n=1}^{nn} \sum_{t=1}^{T} H_{p,j,t} \tag{6}$$

where $H_{p,j,t}$ is the pressure head at node j at time step t (m); and nn is the total number of demand nodes.

2.2.1.5. Water age. The age of water affects its water chemistry by depleting the concentration of residual disinfectants, increasing the total organic carbon and decreasing the dissolved oxygen content of water (Zeidan *et al.* 2021). The likelihood of contaminant formations increases when biofilms attached to pipe walls interact with the bulk flow, especially as the water retention time within the pipe increases (Wang *et al.* 2014). The retention time may increase in the DMA design process due to pipe closures. The objective of minimising the average water age is to reduce the impact of sectorisation.

$$\text{Min (average water age)} = \frac{1}{nn \times T} \sum_{n=1}^{nn} \sum_{t=1}^{T} \mathrm{WA}_{j,t} \tag{7}$$

where $\mathrm{WA}_{j,t}$ is the water age for node j at time step t (h); and nn is the total number of demand nodes.

2.2.2. Constraints

The objectives are optimised under a set of constraints, which include tank regulation, nodal head requirements and hydraulic analysis constraints, as follows:

2.2.2.1. Minimum head requirements. The minimum head constraint is imposed to prevent a demand deficit caused by pipe closure action. This constraint can be applied to either all nodes or only a few selected essential nodes, depending on a careful review of the system's architecture. In this study, nodal heads are assessed for all nodes in the network. The minimum head constraint is given by:

$$H_{j\ \min} \leq H_j\ ; \quad j = 1, \ldots .\ n \tag{8}$$

where, $H_{j\,\min}$ is the minimum required pressure head at node j; and H_j is the available pressure head at node j.

2.2.2.2. Hydraulic constraints. In addition to considering the nodal head constraint, the hydraulic modelling software (EPANET 2.2) used in this study also incorporates flow continuity and energy conservation constraints. The flow and energy conservation constraints are mathematically expressed as follows (Bhave & Gupta 2006):

$$\sum_{l \text{ incident on } j} Q_l - q_j = 0\ ; \quad j = 1, \ldots ., \ n \text{ (flow continuity constraint)} \tag{9}$$

$$\sum_{l \in \mathrm{y}} h_{\mathrm{l}} + \sum E_p = 0; \quad y = 1,\ \ldots .,\ Y \text{ (energy conservation constraint)} \tag{10}$$

where Q_l is the discharge in pipe l; q_j is the nodal demand at node j; n is the number of demand nodes; h_l is the head loss in pipe l; E_p is the energy added to water by a pump; and Y is the total number of loops.

2.2.2.3. Tank level constraints. If the network includes tanks, it is crucial to consider the tank levels during the design of the DMAs. The water level in the tank should always be maintained within the minimum and maximum values. The tank level constraint is enforced in the optimisation problem for networks that have tanks. Mathematically, it is expressed as:

$$TL_{\min j} \leq TL_{tj} \leq TL_{\max j} \tag{11}$$

where $\mathrm{TL}_{\min\ j}$ and $\mathrm{TL}_{\max\ j}$ represent the minimum and maximum allowable levels for tank j, respectively; and $\mathrm{TL}_{t\ j}$ denotes the water level of tank j at time t.

2.2.2.4. Optimisation tool. This study falls into the category of many-objective optimisation as it addresses five objectives. Many-objective optimisation methods, such as Agent Swarm Optimisation (ASO) (Campbell *et al.* 2016), and evolutionary many-objective tools, namely the Borg multi-objective evolutionary algorithm (Borg MOEA), have previously been used to solve boundary identification problems in the design of DMAs (Hadka & Reed 2013; Zhang *et al.* 2017; Liu & Lansey 2020). For DMA design, the communities (or clusters) identified in the clustering phase must be isolated from one another by limiting the connections between adjacent DMAs. To achieve this, the NSGA-III algorithm (Deb & Jain 2014) is used in this work to simultaneously optimise the five objectives described in the preceding section. The decision variables in this study are: (a) the status of the boundary pipes (open/closed), where the open and closed boundary pipes imply the installation of flow meters and isolation valves, respectively; and (b) the pump speed coefficients for each of the operating time steps, including zero for the shutdown. The pump power will also alter when the pump speed changes. The nature of an individual chromosome is explained as follows: If a single chromosome has 10 potential boundary sites for boundary identification and 24-time steps for pump speed variation, the total length of the chromosome will be 34 genes. The first 10 genes will be binary variables ranging from 0 to 1, determining the status of boundary pipes (open/closed). The remaining 24 genes will be continuous variables ranging from 0 to 1, and they will determine the pump speed at various time intervals. The variable for pipe status can be represented as follows:

$$x_{\mathrm{b}} \in \{0, 1\}^{n_{\mathrm{b}}} \tag{12}$$

where x_{b} is the binary variable; n_{b} is the total number of binary variables. When $x_{\mathrm{b}} = 0$, it represents the boundary pipe status as closed, and when $x_{\mathrm{b}} = 1$, the boundary pipe status is open, and a flow meter is installed on it. Similarly, the variable representing the pump status can be expressed as follows:

$$x_{\mathrm{c}} \in \{0, 1\}^{n_{\mathrm{c}}} \tag{13}$$

where x_{c} is the continuous variable; n_{c} is the total number of continuous variables. When $x_{\mathrm{c}} = 0$, then the pump is fully shut off, and when $x_{\mathrm{c}} = 1$, then the pump is operating at its full speed. When $0 < x_{\mathrm{c}} < 1$, then the pump is operating at an intermediate speed.

To summarise, the many-objective optimisation problem of DMA design can be represented in a standard form as follows, with objective function(s), constraints and variable definitions:

- Minimise Obj. cost function (CF) – operational cost – average pressure – water age
- Maximise Obj. RI
- Subject to flow continuity (Equation (9))
- Energy conservation (Equation (10))
- Tank level constraint (Equation (11))
- Lower and upper bounds for variables (Equation (12) and (13))

2.2.2.5. Optimisation tool implementation. The optimisation is accomplished using the NSGA-III algorithm, which is implemented in the C programming language. The code for the algorithm can be found at https://github.com/lfarizav/NSGA-III. The implementation was done in Microsoft Visual Studio 2013. The EPANET 2.2 Programmer's Toolkit, provided by the United States Environmental Protection Agency (USEPA) (https://www.epa.gov/water-research/epanet), consists of dynamic link library (DLL) files and header files. These files were imported into Microsoft Visual Studio 2013 and used for hydraulic analysis. Readers can refer to the EPANET 2.2 Programmer's Toolkit Manual to gain a better understanding of its use.

2.3. Multiple attribute decision-making

MADM is a method for resolving problems with a limited number of options. It describes how the attributes are analysed to arrive at a decision. MADM approaches include the simple additive weighing (SAW) method, the analytic hierarchy process (AHP) method, the technique for order performance by similarity to ideal solution (TOPSIS) method and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method (Rao 2007). A comprehensive review of multi-criteria decision-making can be found in Bruen (2021).

The SAW approach (Fishburn 1967) is used to make decisions in this study. It is the basic, yet widely adopted, MADM approach in practice. Every weighted attribute is considered when evaluating each alternative. The following formula calculates an alternative's composite performance score:

$$P_i = \sum_{j=1}^{M} w_j (m_{ij})_{\mathrm{normal}} \tag{14}$$

where $(m_{ij})_{\mathrm{normal}}$ is the normalised value of attribute using linear transformation; i and j represent the alternative and attribute, respectively; w_j is the weight assigned to a given attribute and P_i is the overall score of the alternative i.

The assignment of weights (w_j) is based on simple logic. For example, if there are five attributes in decision-making, then initially, all the attributes have equal weightage, i.e. 0.2. Subsequently, the weight assigned to each individual attribute will either be increased above 0.2 or decreased below 0.2, depending on the user's preference for each attribute. At times, it may be possible for an attribute to fluctuate within a very narrow range for different alternatives. In such cases, smaller weights or even zero weights can be assigned without affecting the overall decision-making process.

The best choice is the one with the highest value of P_i, which ranges from 0 to 1. The normalisation of attribute values can be categorised based on cost criteria or negative criteria, as well as benefit or positive criteria (Liu & Han 2018). As a result, the normalisation equation can be modified according to specific needs. For cost criteria, like water age, operational cost, number of flow meters and average pressure, the normalisation of attribute j for alternative i is:

$$(m_{ij})\text{normal} = \frac{m_{ij\max} - m_{ij}}{m_{ij\max} - m_{ij\min}} \tag{15}$$

For benefit criteria, like the RI, the normalisation equation becomes:

$$(m_{ij})\text{normal} = \frac{m_{ij} - m_{ij\min}}{m_{ij\max} - m_{ij\min}} \tag{16}$$

where $m_{ij\max}$ and $m_{ij\min}$ are the maximum and minimum values of attribute j for alternative i; and m_{ij} is the i^{th} alternative solution of attribute j.

3. COMPUTATIONAL RESULTS

The application of the methodology is presented in this section, using two benchmark water networks of different complexities. The example networks are the Wolf network (a modified version of the Colorado Springs network) and the MMOD network (a modified version of the Modena network) (Zeidan *et al.* 2021).

3.1. Network 1: Modified Wolf network

The first example network is the modified Wolf network, as shown in Figure 2(a). There are four constant-head sources, six pumping stations and 1.782 junctions in the system. In this example, there are no storage tanks. Figure 3 shows the demand pattern used in this study. The energy tariff coefficients used in operational cost optimisation are tabulated in Table 1.

Application of FNA for community identification, using average pressure as pipe weights, resulted in the identification of 23 communities and 63 interconnecting pipes (see Figure 2(b)). The modularity value of 0.92 indicates a healthy partitioning of the water network. The FNA was used solely as a clustering tool, regardless of the highest modularity configuration.

The pumps in all the case studies are assumed to follow the same pattern. They represent a 24-h schedule for all the pumping stations. A minimum desired pressure of 30 m was set for all the demand nodes. The population size and maximum number of generations in an evolutionary algorithm have a substantial impact on the optimisation process in terms of its outcomes and running times.

For the implementation of NSGA-III on the modified Wolf network, a population size of 240 and 40 generations was used. The many-objective genetic algorithm is applied to the network layout, resulting in different trade-off solutions. The total run time recorded for the modified Wolf network was 65 min. It is important to note that the solutions obtained with evolutionary

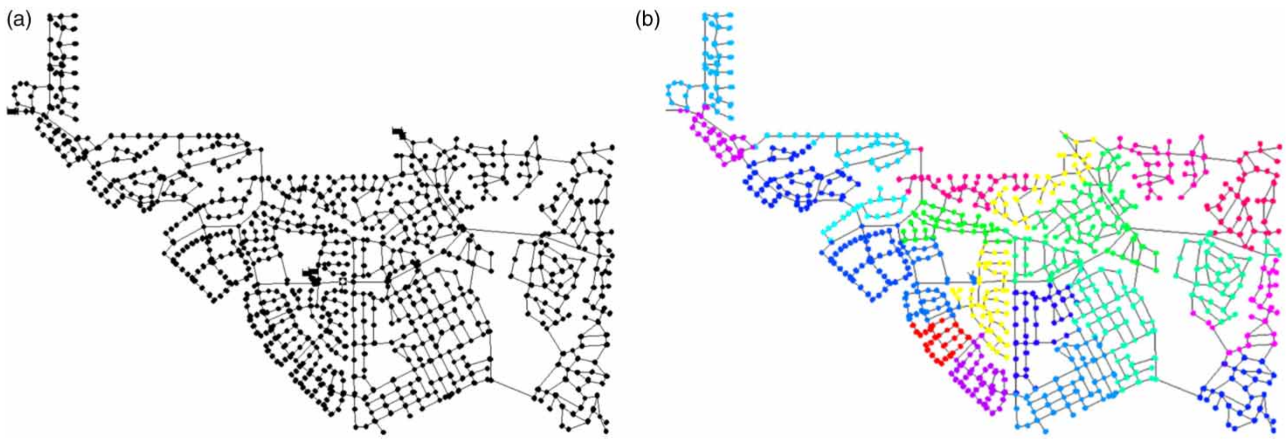

Figure 2 | (a) Wolf raw network; (b) 23 cluster configuration.

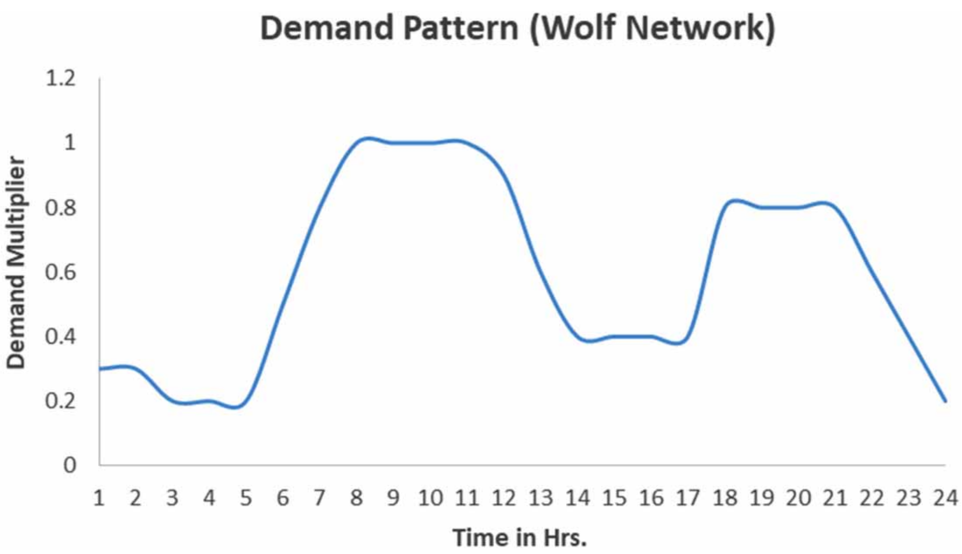

Figure 3 | Demand pattern used in the study.

Table 1 | Energy tariff coefficient for various times in a day

Time in hours	Energy tariff coefficient
12:00–6:00 am	0.25
6:00 am – 12:00 pm	0.8
12:00–6:00 pm	1.5
6:00 pm – 12:00 am	0.6
Base energy tariff used	**0.16 $/kW-h**

algorithms are not always the most precise or ideal for the situation at hand. In most cases, a solution that is decent enough will suffice. The relationship between each of the five objectives is depicted in various two-dimensional objective value planes in Figure 4(a)–4(j). It is crucial to acknowledge that the graphics are intended to analyse the trade-offs between objectives in different two-dimensional objective value planes.

It can be clearly seen from Figure 4(a)–4(d) that the number of flow meters has an impact on the other four objectives. The identification of boundaries involves the closure of a few pipes. This reduces the mutual interaction between the clusters, which facilitates the operational management of the water network. The water must take longer routes to reach the demand nodes, which causes a change in the original network configuration. If more boundary pipes are kept open, it reduces the operational costs of the pump, as shown in Figure 4(a). Additionally, it is advantageous in terms of maintaining the average pressure in the network, as depicted in Figure 4(b). The total number of flow meters in the set of optimal solutions ranged from 33 to 44, and the operational cost ranged from $121,008 to $513,620. The average pressure of the network ranged from 67.14 to 69.48 m. In terms of the RI, the frictional losses decrease with an increase in the number of flow meters. In this case, the RI fluctuated within a narrow range (0.83–0.90) as the number of flow meters increased (Figure 4(c)). The water age was less affected by the capital cost (number of flow meters) or the operational cost. It fluctuated within a narrow range (6.89–7.18 h) with a wide variety of flow meters (Figure 4(d)). The network was disturbed minimally in terms of its hydraulic, energy and quality aspects. This may be due to two reasons: the highly looped nature of the Wolf network and the scheduling of pump speeds.

The pump scheduling problem followed the same set of constraints, which helped maintain sufficient energy for the desired flows. Figure 4(e) shows an increasing trend in the average pressure on the network as the operational cost increases. The

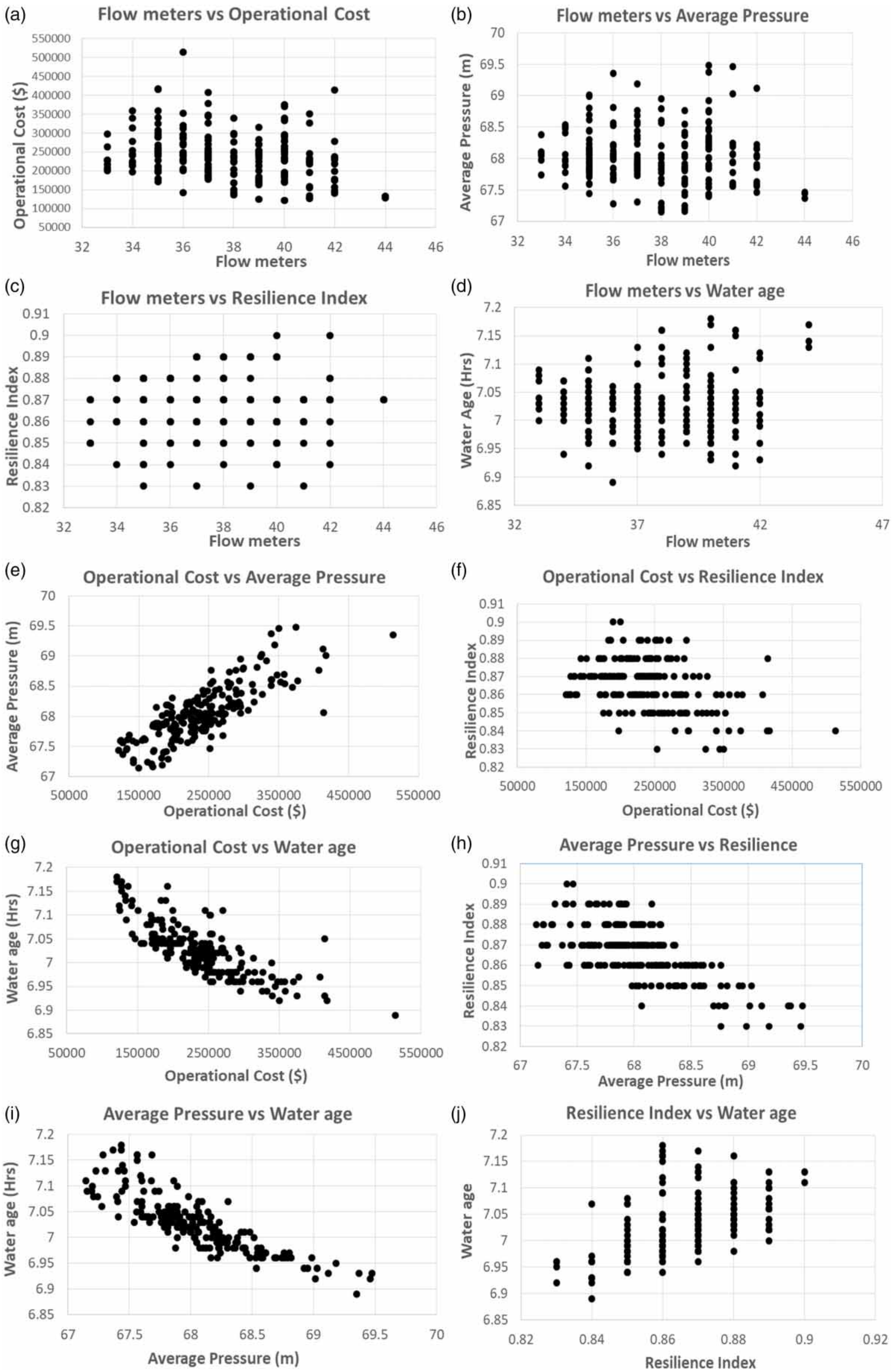

Figure 4 | Results of NSGA-III optimisation for the Wolf network.

head losses caused by pipe closures were offset by the pressure generated by pumps. Figure 4(f) and 4 show the relationship between operational cost and RI, as well as water age. It is important to check for any significant changes in the water age when fixing the boundary pipe status. In this case study, the water age did not deteriorate significantly from an engineering perspective. Figure 4(i) exhibits the relationship between water age and average pressure, demonstrating a clear trend of decreasing water age as average pressure increases. Figure 4 displays a relationship between resilience and average pressure. Specifically, an increase in average pressure leads to an increase in the RI of the network. Additionally, Figure 4(j) demonstrates that the water age decreases as the RI improves. In order to select a single solution from a set of feasible solutions, MADM was applied. In this regard, the first 15 solutions were sorted based on the increasing order of operational costs, as shown in Table 2.

In order to employ MADM, the table is converted into a normalised decision matrix (Table 3). The number of flow meters, operational cost, average pressure and water age are treated as cost criteria, while the RI is treated as a benefit criterion. Different weights were assigned to each objective, and a final score was evaluated using the SAW method. Initially, all the alternatives (objectives) were assigned equal weights of 0.2. However, iteratively, these weights changed, with the highest weights being assigned to the objectives related to cost. The optimal solution achieved a final score of 0.65 and is indicated in Table 3.

For this solution, a total of 23 pipes were closed out of 63 boundary pipes, and 40 flow meters were required. The operational cost was $121,008.77, with an average pressure of 67.432 m. This configuration had a high resilience of 0.86 and a relatively poor water age, i.e., 7.17 h.

Zeidan *et al.* (2021) presented graphical results for cluster configurations of 5, 10, 20 and 46 for the modified Wolf network. The water age approximately ranged from 7 to 7.6 h for all configurations, while the proposed method achieved a slight improvement (6.89–7.18 h). Zeidan *et al.* (2021) reported operational costs ranging from $100,000 to $2,400,000 (approximately), with most trade-offs concentrated in the range of $100,000–$500,000. The proposed method obtained solutions with operational costs ranging from $121,008 to $513,620. The average pressure in the network obtained by the proposed method was 67–69 m, whereas, in Zeidan *et al.* (2021), the average pressure varied in the range of 30–60 m (approximately.). Due to variations in objectives, clusters and genetic parameters used, making an exact comparison between the two multi-objective studies is challenging. The results obtained from the proposed method and the study conducted by Zeidan *et al.* (2021) demonstrate similar trends, providing additional evidence of their accuracy. Although the absolute values differ, the consistent patterns suggest a reliable outcome for the studied network.

Table 2 | First fifteen sorted trade-off solutions obtained from boundary optimisation for the Wolf network

Sr No.	Number of flow meters	Operational cost in $	Average pressure (m)	Resilience index	Water age (h)
1.	40	121,008.77	67.432	0.86	7.17
2.	40	121,046.16	67.432	0.86	7.18
3.	39	124,014.63	67.593	0.86	7.12
4.	39	124,647.40	67.600	0.86	7.11
5.	41	127,043.01	67.565	0.86	7.16
6.	41	127,107.54	67.565	0.86	7.16
7.	41	127,156.21	67.565	0.86	7.15
8.	44	127,203.44	67.368	0.87	7.17
9.	44	132,490.16	67.446	0.87	7.14
10.	44	132,958.09	67.460	0.87	7.13
11.	41	134,215.74	67.615	0.86	7.09
12.	38	136,708.41	67.685	0.86	7.16
13.	42	141,476.53	67.593	0.87	7.12
14.	38	142,035.56	67.228	0.87	7.13
15.	36	142,677.22	67.277	0.88	7.06

Table 3 | Normalised matrix of trade-off solutions for the Wolf network

Sr No.	Number of flow meters	Operational cost	Average pressure	Resilience index	Water age	Final score
1.	***0.50***	***1.00***	***0.55***	***1.00***	***0.08***	***0.65***
2.	0.50	1.00	0.55	1.00	0.00	0.64
3.	0.63	0.86	0.20	1.00	0.50	0.63
4.	0.63	0.83	0.18	1.00	0.58	0.63
5.	0.38	0.72	0.26	1.00	0.17	0.49
6.	0.38	0.72	0.26	1.00	0.17	0.49
7.	0.38	0.72	0.26	1.00	0.25	0.50
8.	0.00	0.71	0.69	0.50	0.08	0.42
9.	0.00	0.47	0.52	0.50	0.33	0.35
10.	0.00	0.45	0.49	0.50	0.42	0.35
11.	0.38	0.39	0.15	1.00	0.75	0.45
12.	0.75	0.28	0.00	1.00	0.17	0.40
13.	0.25	0.06	0.20	0.50	0.50	0.24
14.	0.75	0.03	1.00	0.50	0.42	0.51
15.	1.00	0.00	0.89	0.00	1.00	0.58
Weights	0.25	0.3	0.2	0.1	0.15	1

The bold and Italic values in this table indicate the best solution obtained by applying SAW method.

3.2. Network 2: Modena network

The second case study is the Modena Network, which is a well-established network in the research community. The modified version of the Modena case network (MMOD Network) (Zeidan *et al.* 2021) is used in this work. It consists of 270 nodes, 316 pipes, 4 reservoirs, 4 pumps and 1 tank, as shown in Figure 5(a). This network follows the same demand pattern as indicated in Figure 3 and the tariff pattern as given in Table 1. The FNA implementation on the network, based on average pressure as pipe weights, resulted in 6 clusters and 25 boundary pipes, with a modularity index of 0.8. The configuration of the six clusters is shown in Figure 5(b). The input parameters for the genetic algorithm were a population size of 240 and 40 generations. The nodal pressure requirements were set at 30 m.

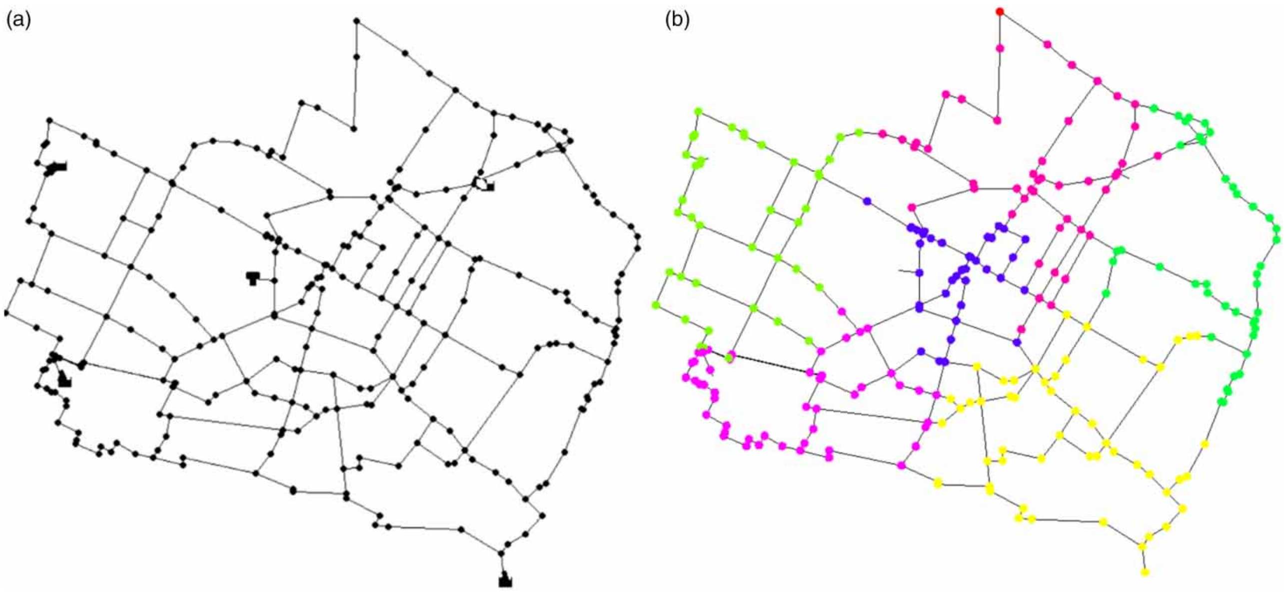

Figure 5 | (a) MMOD raw network; (b) 6 cluster configuration.

The application of the NSGA-III algorithm resulted in several trade-off solutions. Figure 6(a)–6(f) is presented to illustrate the trade-offs between the objectives in various two-dimensional objective value planes. The total run time recorded for the MMOD network was 28 min. The results showed that the number of flow meters ranged from 14 to 21 in all of the feasible solutions. The operational cost ranged from $277,932 to $341,095. The average pressure ranged from 64.91 to 91.82 m for different flow meters and operational costs. The RI and water age varied within a narrow range of 0.42–0.45 and 1.06–1.19 h, respectively. Such minor range alterations are given less importance during the decision-making process.

The operational cost is observed to decrease with an increasing number of flow meters (Figure 6(a)). This is because a greater number of open boundary pipes allow the water to reach the demand nodes directly without increasing the head loss. This also helps maintain the average pressure of the network (Figure 6(b)). The water age also improved with a greater number of open boundary pipes, but only within a small range (Figure 6(c)).

This indicates that a similar water age can be obtained with varying numbers of flow meters. Hence, it is not correlated with the overall cost aspect. Figure 6(d) shows a linear increase in average pressure with operational cost due to the obvious

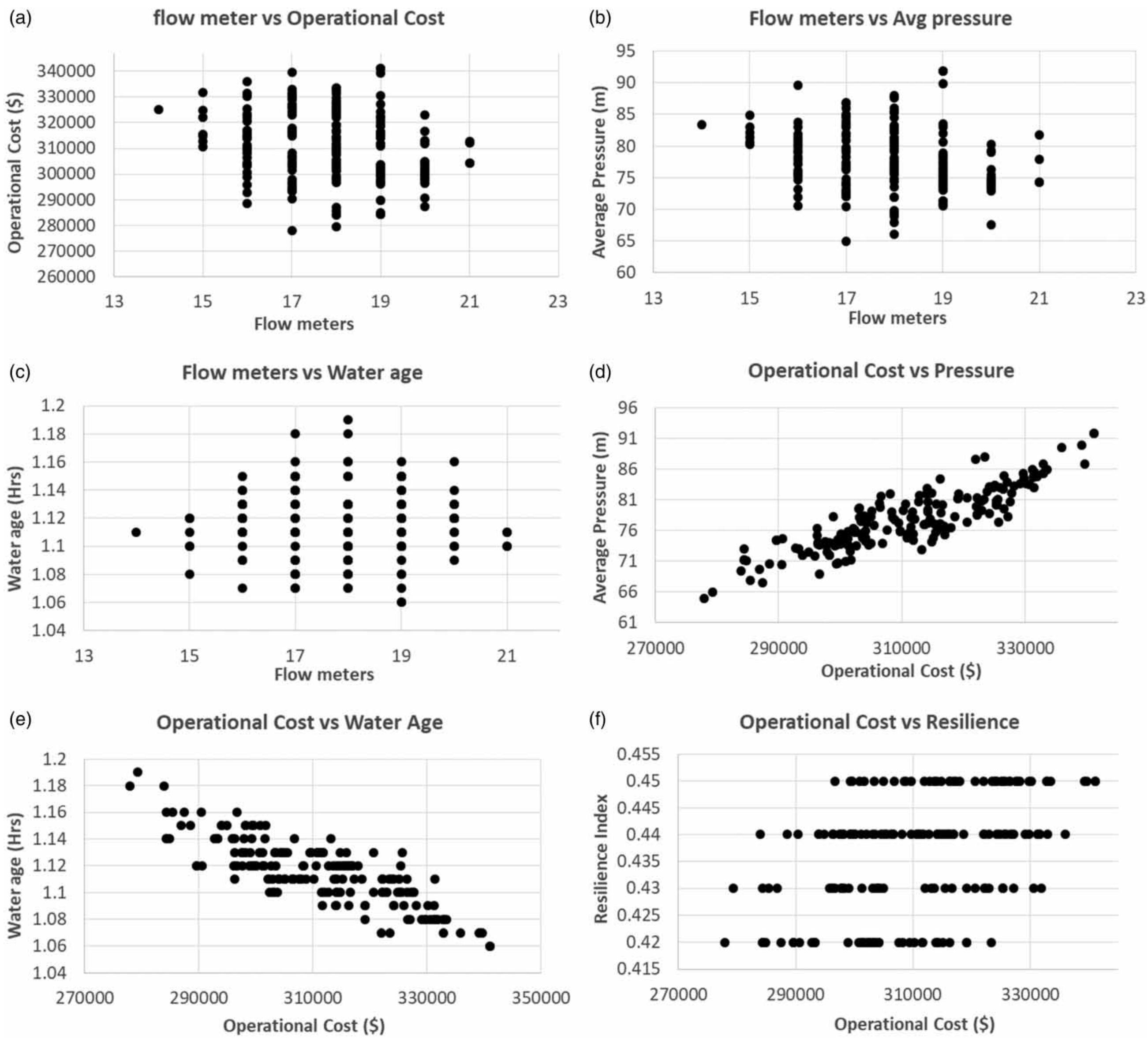

Figure 6 | Results of NSGA-III optimisation for the MMOD network.

reasons for the increased pumping rate. Figure 6(e) shows the inverse relationship between operational cost and water age in the network. An increase in operational costs leads to a reduction in water age. Figure 6(f) illustrates that the RI improves with an increase in operational costs.

Similar trends were also observed in the first case study, indicating that the methodology adopted for boundary optimisation yields reasonable results within the specified constraints.

Table S1 (see supplementary material for Tables S1, S2 and S3) displays the first 15 solutions arranged in ascending order of operational cost. The objectives (or alternatives) were normalised based on the cost and benefit aspects, and the SAW method was implemented. The optimal solution obtained had a final score of 0.76 (Table S2). This solution indicates that 17 flow meters need to be installed, and 8 pipes need to be closed out of a total of 25 boundary pipes. The operational cost is $277,932, with an average pressure of 64.91 m.

The performance of the final solution has also been analysed to gain better insights into the hydraulics of individual DMAs. The mean, minimum and maximum pressure values of the individual DMAs are shown in Table S3.

It is worth noting that Zeidan *et al.* (2021) also utilised FNA for clustering in the same MMOD network. However, they did not take pipe weights into account and reported 5 clusters with 25 boundary pipes. In contrast, our proposed method, which incorporates pressure as pipe weights, yielded 6 clusters and 25 boundary pipes. An additional DMA can be obtained without increasing the number of boundary pipes using the proposed method. The clustering results obtained for the proposed methodology are in line with the basic principle of DMA design, which is to partition the network into the maximum number of DMAs with minimum interconnections between them.

In the boundary optimisation phase, Zeidan *et al.* (2021) considered three objectives: pump operational cost, excess pressure and water age, using NSGA-II optimisation. The boundary optimisation resulted in 21 closed boundary pipes and 4 open boundary pipes. However, the proposed methodology included two additional objectives: the number of flow meters and the RI. This methodology used NSGA-III optimisation, which resulted in 8 closed pipes and 17 open pipes. The greater number of closed boundary pipes seems beneficial in terms of the initial cost of device installation (flow meter cost). In such cases, the water has to take a longer route to reach the desired nodes, resulting in increased head loss and water age. To mitigate such losses, additional pumping may be required. The operational cost for Zeidan *et al.* (2021) ranged approximately from $245,000 to $358,000, with a water age in the range of 1.9–2.1 h. The mean pressure ranges from 100 to 145 m (approximate values extracted from the graphs presented in the study). For the proposed methodology, the operational cost ranged from $277,932 to $341,095; the average pressure ranged from 64.91 to 91.82 m; and the RI and water age varied within a small range of 0.42–0.45 and 1.06–1.19 h, respectively. The findings of both studies were similar in terms of trends, namely an increase in average pressure with an increase in operational cost and a decrease in water age with an increased pumping cost. The discrepancy in the results of the two studies may be attributed to the variation in boundary pipes and their combination of open/closed status in each case.

Another reason may be related to the optimisation parameters used and the size of the search space. As the search space increases with the number of objectives, there is no guarantee that the solutions obtained will be the most accurate. However, in most cases, good enough solutions are obtained. The multi-objective studies provide a variety of solutions for a given problem. Fixing the boundary pipe status using a heuristic method outside the optimisation process restricts optimality and completeness. Nevertheless, it eases computational efforts. The proposed method utilises the full potential of the search space and directs the search towards feasible alternatives. As there are multiple objectives in this study, the proposed method works efficiently and provides clear trends in Pareto optimal solutions for large networks as well.

For small networks, the search space is limited, resulting in a limited number of alternative solutions. The idea here is to extend the previous work on the DMA's design for pump scheduling optimisation, considering the cost of implementation, and to explore the possibilities of a wide range of trade-off solutions. This will be achieved by including the evaluation of the RI, water quality aspects and pressure regulation in the optimisation process. Lastly, it can be said that the proposed methodology can reasonably identify DMAs and offers flexibility to the user to select a single solution from the set of feasible solutions.

4. CONCLUSION

DMA formation is a challenging task as it requires considering several objectives simultaneously. However, these objectives also change with the type of network, in addition to other considerations. This study presents a method for designing DMAs using many-objective optimisation. The goal is to optimise the five objectives: the number of flow meters, operating costs, mean pressure, mean water age and the RI. This method is specifically designed for networks that include pumps. Two separate examples of applications with varying degrees of complexity were investigated, and trade-offs among the five objectives were analysed to reveal the optimisation potential of the system. The novel contribution of this study is in laying out and solving a many-objective optimisation problem that incorporates five objectives within one framework. This method provides flexibility in selecting one solution from various trade-off alternatives using a multi-criteria decision-making technique. Future steps for this work include reducing the sample size of the variables, employing additional objective optimisation methods and exploring dynamic DMA boundaries to improve resource utilisation.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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